

# Susceptibility assessment of shallow slides failure and run-out

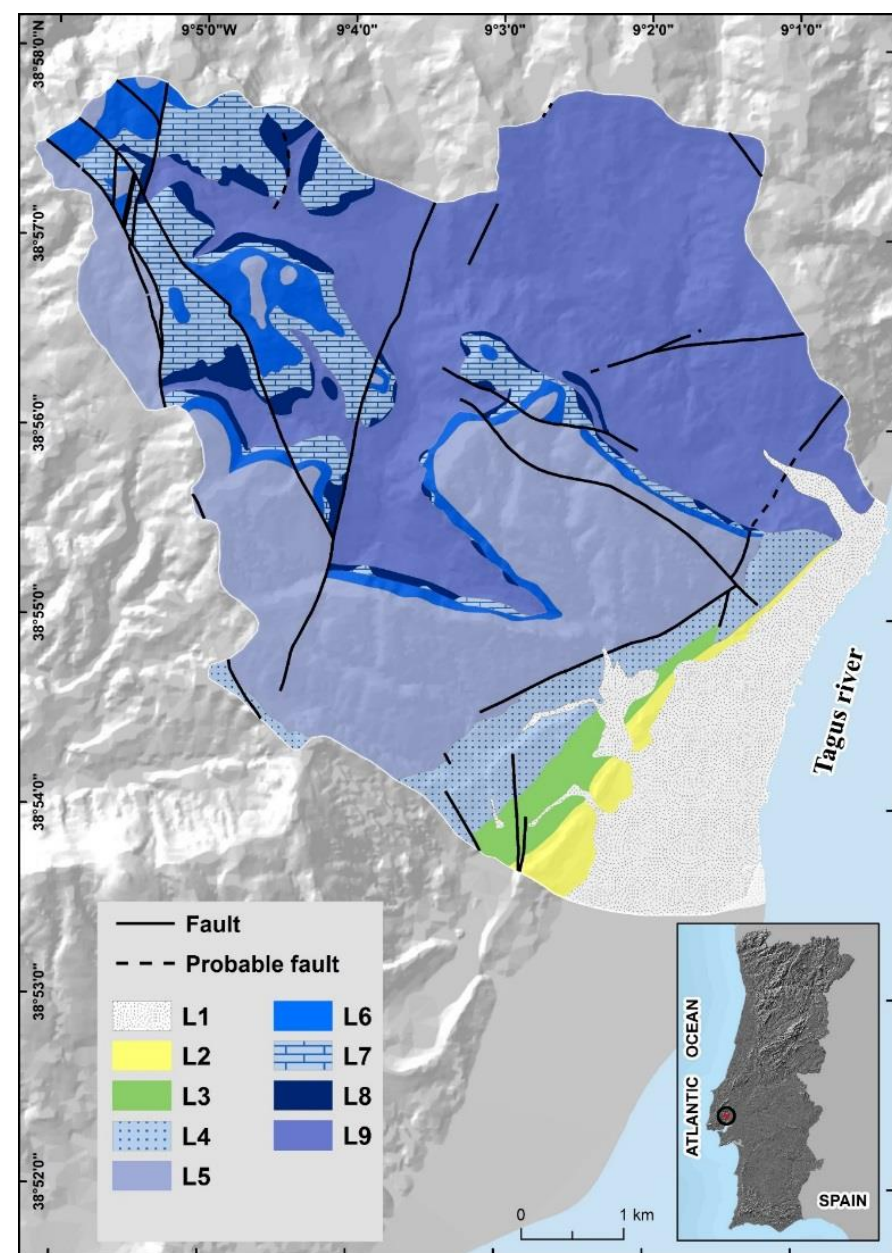
Raquel Melo<sup>1</sup>, José L. Zêzere<sup>1</sup>, Jorge Rocha<sup>1</sup>, Sérgio C. Oliveira<sup>1</sup>

<sup>1</sup>Centre for Geographical Studies, Institute of Geography and Spatial Planning, Universidade de Lisboa, Portugal

## 1. Introduction

The integration of landslide initiation and run-out areas has been accepted as an appropriate procedure for landslide susceptibility assessment (e.g. Dai and Lee 2002; Van Westen et al. 2006; Greiving et al. 2014; Melo and Zêzere 2017). In this framework, the susceptibility analysis must be divided into two distinct stages: (1) The first stage is focused on the susceptibility to failure and (2) the second stage refers to the run-out modelling using the initiation areas as an input. Bivariate and multivariate statistical models have been frequently used to define potential failures since they allow quantifying the weight of each variable on the slope instability system as well as to validate the modelling results using success and prediction rates or Receiver Operating Characteristic (ROC) curves. Cellular automata (CA) models have been generally used for the run-out simulation of debris flows and other flow-type movements (e.g. Avolio et al. 2013; Tiranti and Deangeli 2015; Gregoretti et al. 2016). The cellular automata simulation approach refers to a relatively simple and dynamic spatial system, traditionally based on a grid of cells. The value of each cell is determined by the previous value or state of the neighboring cells, according to certain transition rules. The following time step or iteration is always dependent on the previous one and, at the end of the simulation, complex patterns are generated. For this reason, CA models can be efficiently applied to the simulation of complex natural processes. In this research, we present a shallow slide susceptibility assessment in the Silveira and Santo António river basins (region north of Lisbon, Portugal), by modelling the failure and run-out areas separately. The shallow slide failures are evaluated using a statistical method (logistic regression) and for the run-out assessment a simple CA model is proposed. The main objective of this work is to construct a final shallow slide susceptibility map including both failure and run-out areas. Lastly, this work aims to accomplish a combination of low-cost methodology, with limited input data, which allows a good performance of the susceptibility assessment and can be easily applied to other study areas.

## 2. Study area

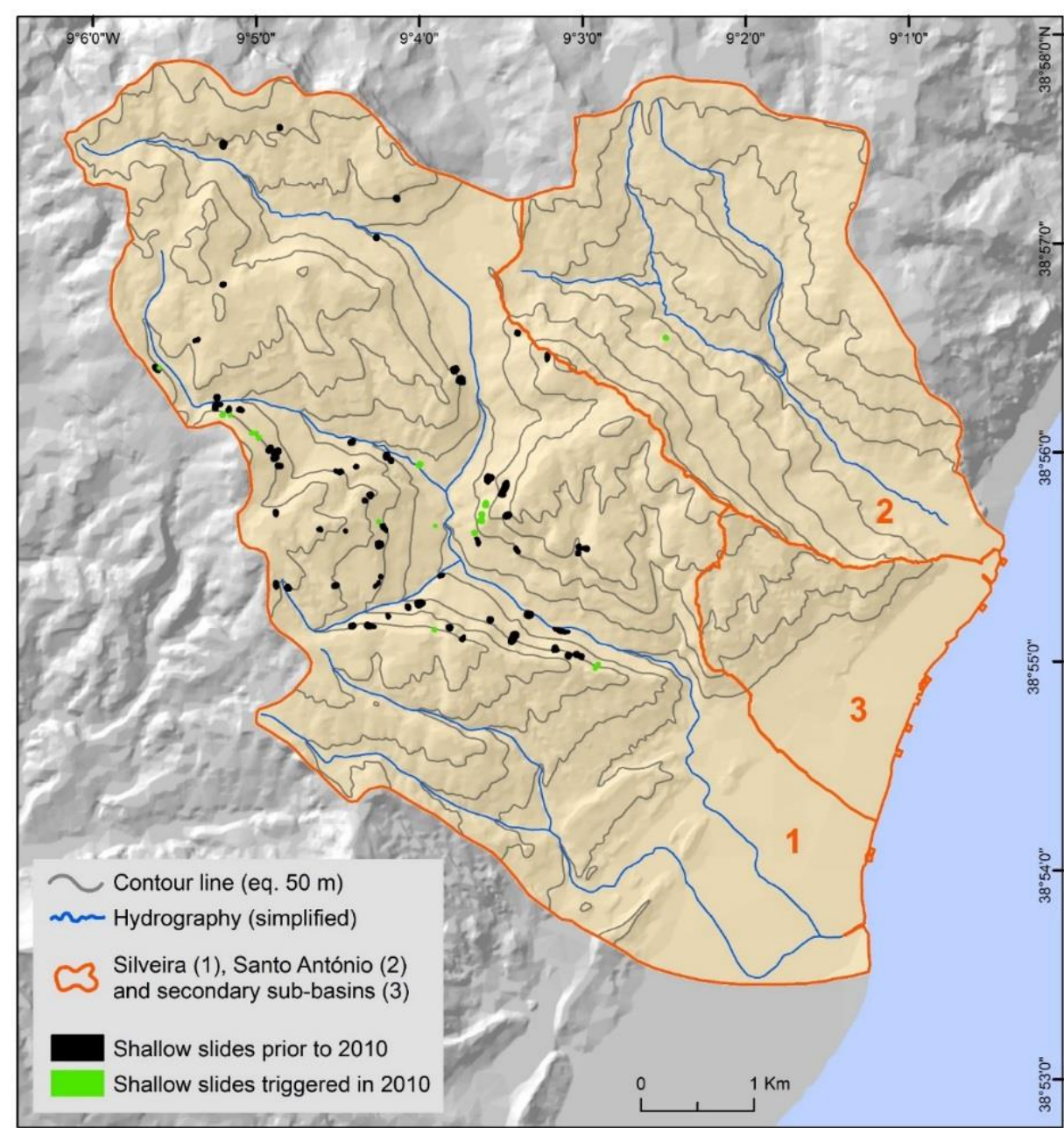


- Extends for ca. 43 km<sup>2</sup>.
- Elevation between 0 and 377 m a.s.l.
- Geological formations mainly of sedimentary nature (Figure 1).
- Slope angle: from 0 to 58° (mean = 10°; STD = 7°).
- 81.5% of the area with slope angles ≤ 15°; 8.8% ≥ 20°.
- Rainfall regime: typically Mediterranean; inter-seasonal and inter-annual high irregularity (long-lasting periods of rainfall or drought; short-duration intense rainfall).
- Shallow slides in the study area triggered by episodes of short-duration intense rainfall, usually between 1 to 15 days (Zêzere et al. 2015).

**Fig. 1** - Location and lithology of the Silveira and Santo António river basins. L1: fluvial deposits, alluvium and landfills; L2: sandstones, mudstones, conglomerates and limestones; L3: marly limestones, sandstones, conglomerates, marls and limestones; L4: sandstones, marls and limestones; L5: limestones and marls; L6: sandstones, marls, limestones and marly limestones; L7: coralline limestones; L8: marls; L9: clays and marls.

## 3. Data, methods and results

### 3.1. Landslide inventory



**Fig. 2** - Inventory of shallow slides in the study area.

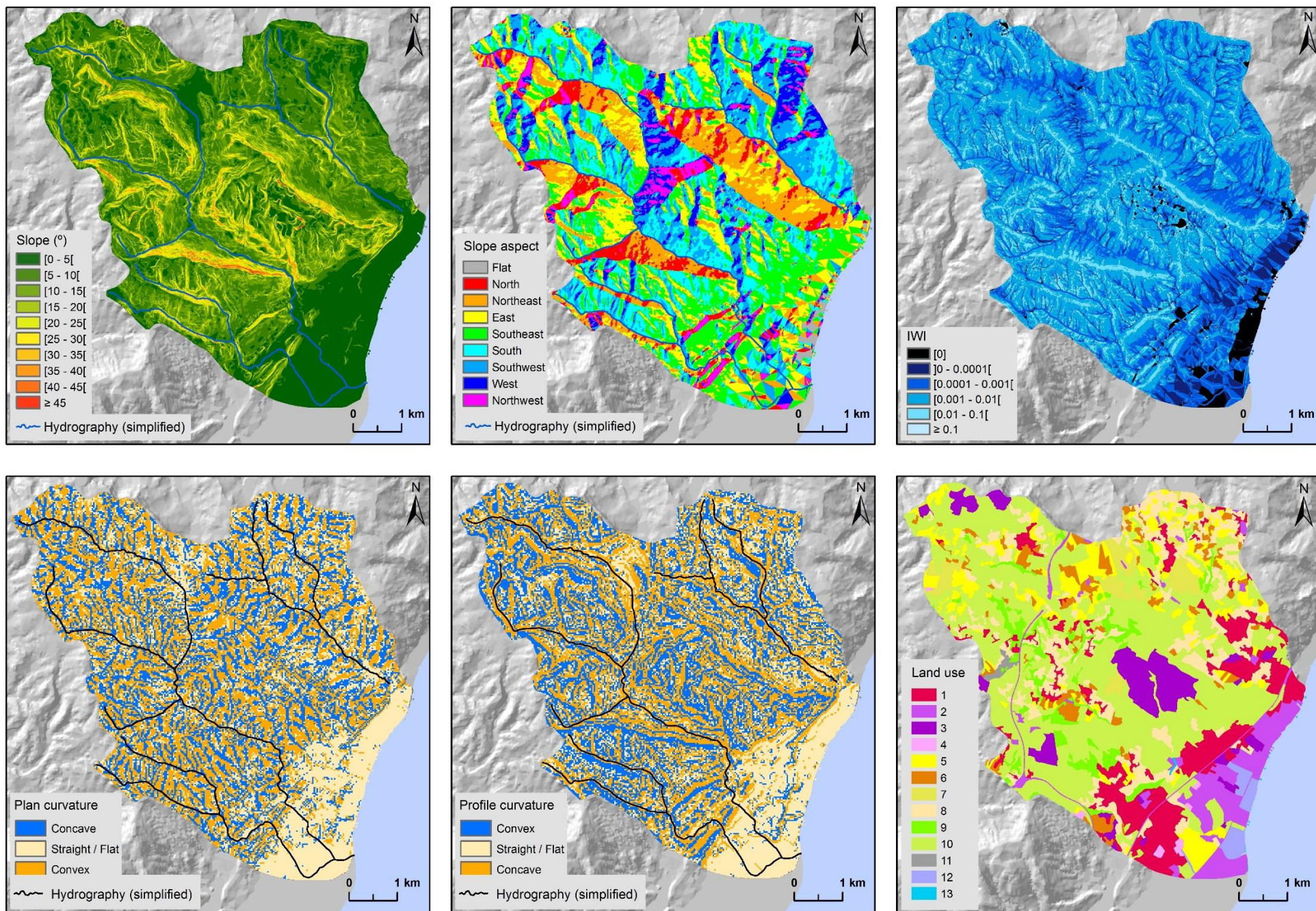
- Landslide inventory: 81 shallow slides (Figure 2).
- 64 shallow slides occurred prior to 2010 (training group)
- 17 shallow slides occurred between January and March 2010 (validation group)
- The depth of the slip surface is typically less than 2.5 m
- As a rule, the shear surface is located at the interface between the soil cover and the bedrock.

The shallow slides inventory was used with two purposes: 1) to evaluate the correlation between the volume of the mobilized material and the accumulation area of the shallow slides; and 2) to validate the susceptibility models to failure and run-out.

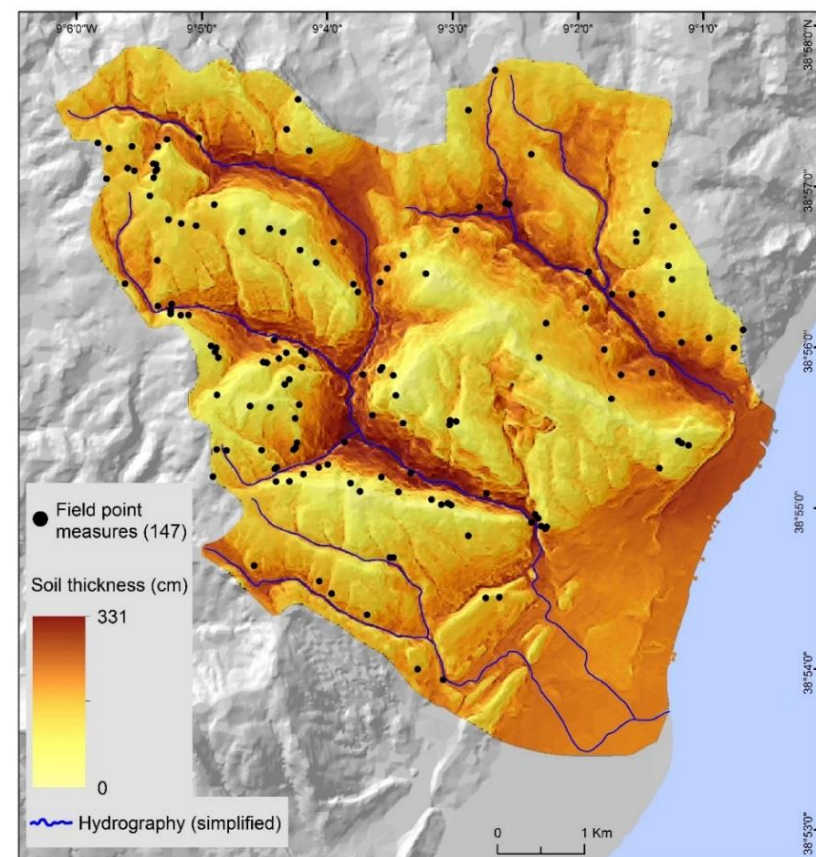
### 3.2. Susceptibility assessment of shallow slides failures

#### 3.2.1. Predisposing factors

The following predisposing factors were selected to assess the susceptibility to shallow slide failure (Figure 1, 3 and 4): slope angle, slope aspect, inverse topographic wetness index (IWI), plan curvature, profile curvature, land use, lithology and soil thickness. All morphometric variables were derived from a Digital Terrain Model (DTM) with a resolution of 5 m. The land use map was obtained from the official map representing the land use in 2007 (1:25,000 scale) and the lithology was derived from the official geological map of the region (1:25,000 scale).



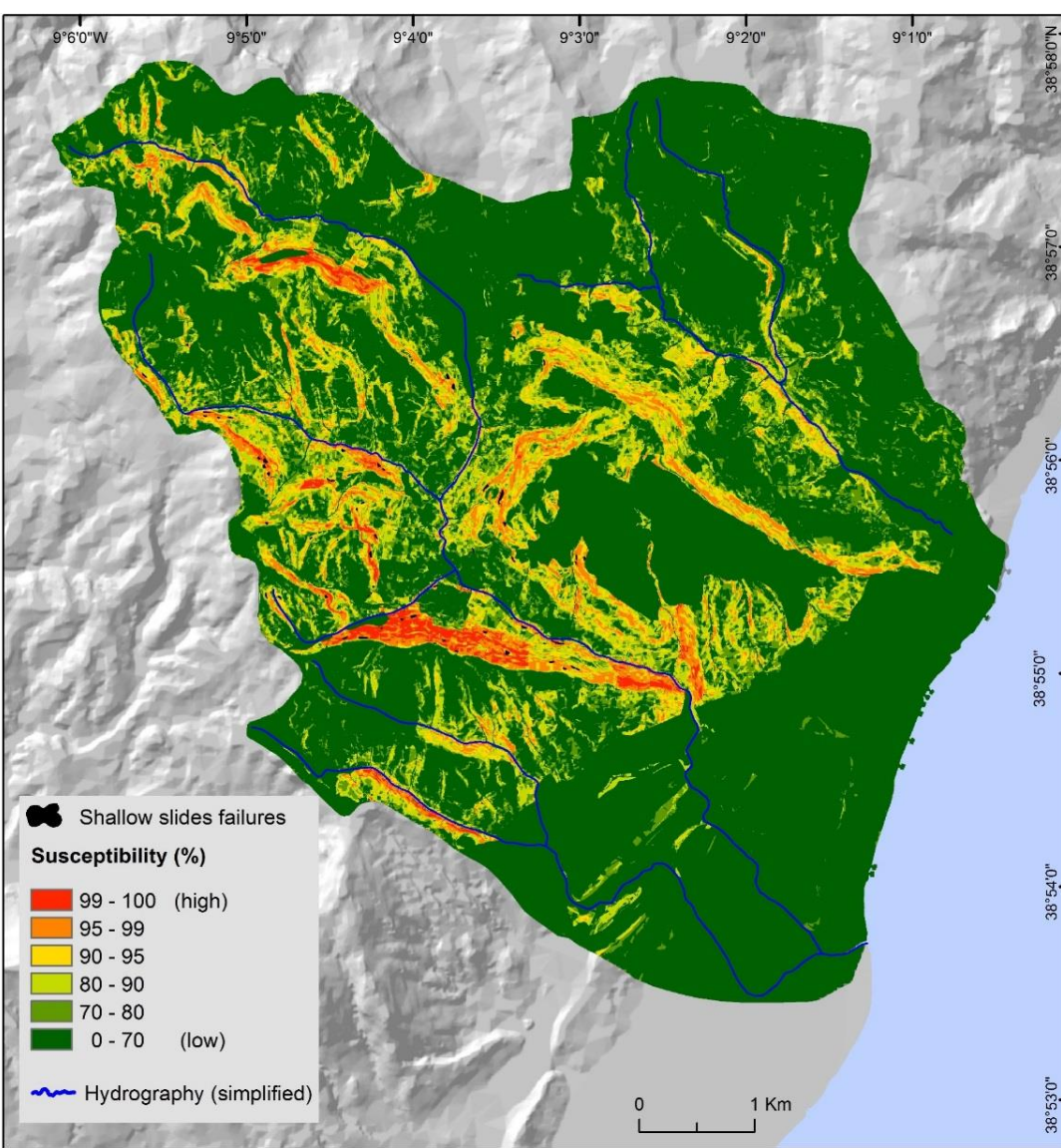
**Fig. 3** - Predisposing factors used as independent variables. Land use: 1) urban areas; 2) industrial, commercial and transport units; 3) mine, dump and construction sites; 4) green urban areas; 5) temporary crops; 6) permanent crops; 7) permanent pastures; 8) heterogeneous agricultural areas; 9) forests; 10) shrub and herbaceous vegetation; 11) open spaces with little or no vegetation; 12) inland wetlands; 13) inland waters.



**Fig. 4** - Soil thickness model (sGIST) for the study area.

#### 3.2.2. The Logistic Regression (LR) shallow slides susceptibility model

The shallow slides-free areas were randomly sampled according to the total number of presences. Fifty LR models were performed and new absence cells (1050) were sampled for each model.



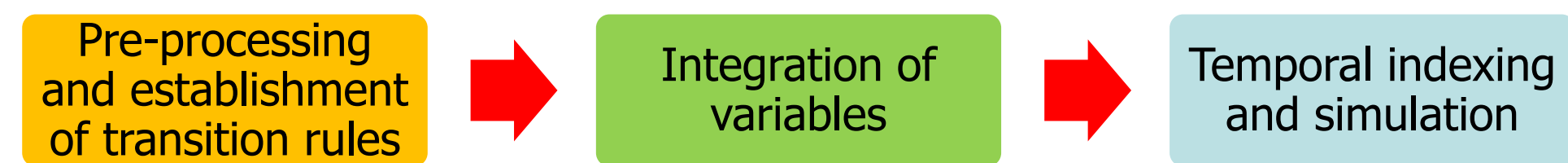
**Fig. 5** - Susceptibility model for shallow slide failures.

The final spatial probability map (Figure 5) results from the mean probability calculated for the 50 LR models.

The predictive capability of the LR model was evaluated through a ROC curve (AUC = 0.90).

### 3.3. Susceptibility assessment of shallow slides run-out

The CA model used to simulate the shallow slides run-out was implemented through the following sequential steps:



#### 3.3.1. Pre-processing and establishment of transition rules

The pre-processing step includes the creation of a database with the modelling inputs: a binary raster file with the shallow slides multi-temporal inventory; and the DTM, from where the slope angle and the slope aspect are extracted.

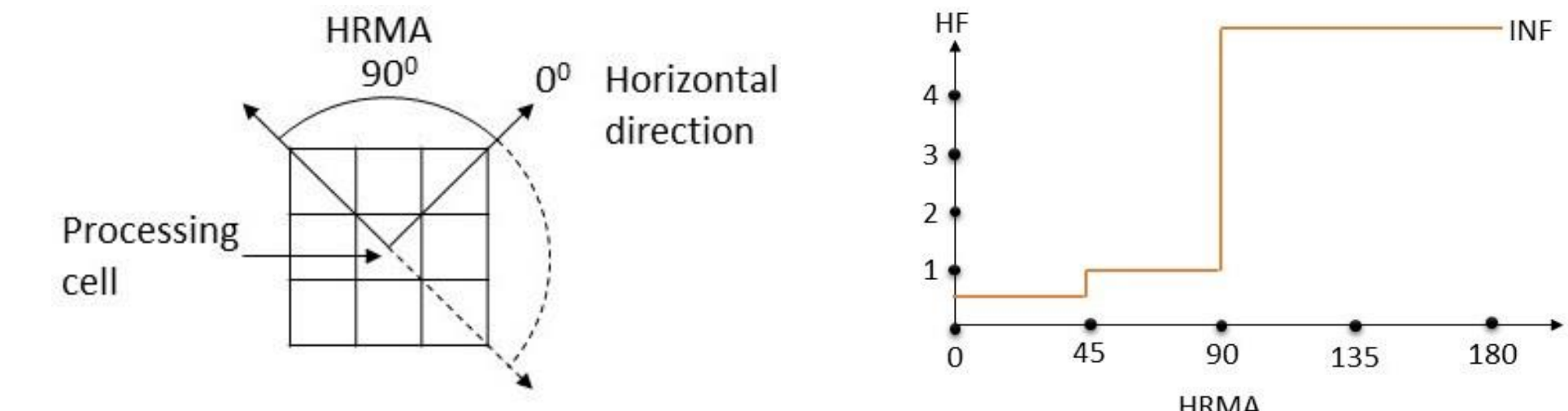
The transition rules are directly related with the motion of the displaced mass. The likely traveling directions are identified, both horizontally – the horizontal factor (HF) – and vertically – the vertical factor (VF). These two factors correspond, respectively, to the slope aspect and to the slope angle (in degrees).

#### 3.3.2. Integration of variables

For the integration of transition rules, the algorithm Path Distance was used (ESRI 2014). To apply Path Distance, three components are required: the cost surface, the HF and the VF.

Cost grid surface: a weight is assigned to each cell, which is proportional to the cost associated with the passage of the landslide displaced mass.

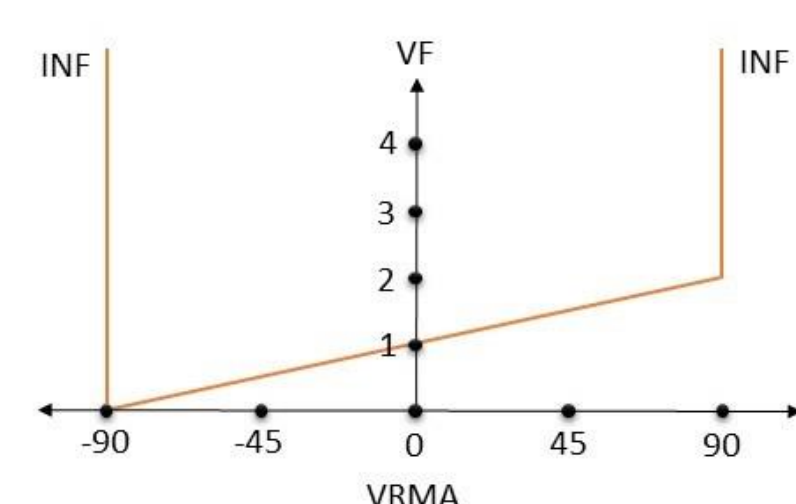
The HF influences the total cost of the movement, being responsible for any horizontal friction found. This factor is calculated in two steps: (i) the horizontal direction is estimated for each cell and the direction with the lowest horizontal cost of movement, regarding the processing cell, is identified; (ii) the HF is determined as the angle between the horizontal direction of a cell and the direction of movement, i.e., the horizontal relative moving angle (HRMA) (Figure 6). For HF calculation, the function forward movement was used (Figure 7), which states that only forward movement is allowed. If HRMA < 45°, the cell's HF is defined as the value associated with the Zero Factor (= 0.5). When HRMA is ≥ 45° < 90°, the HF is defined as Lateral Value (= 1). If HRMA ≥ 90°, the HF is set to ∞. This means that the landslide displaced mass can never move backwards, and the preferential movement takes place at an angle of 45°, since the travel cost between 45° and 90° is twice as high (from 1 to 0.5).



**Fig. 6** - Horizontal relative moving angle (HRMA)

**Fig. 7** - Forward horizontal factor

The VF considers the vertical elements that may affect the movement of the displaced mass from one cell to another. To estimate the VF, the slope angle between two cells is calculated. The resulting value corresponds to the vertical relative moving angle (VRMA) (Figure 8).



**Fig. 8** - Linear vertical factor

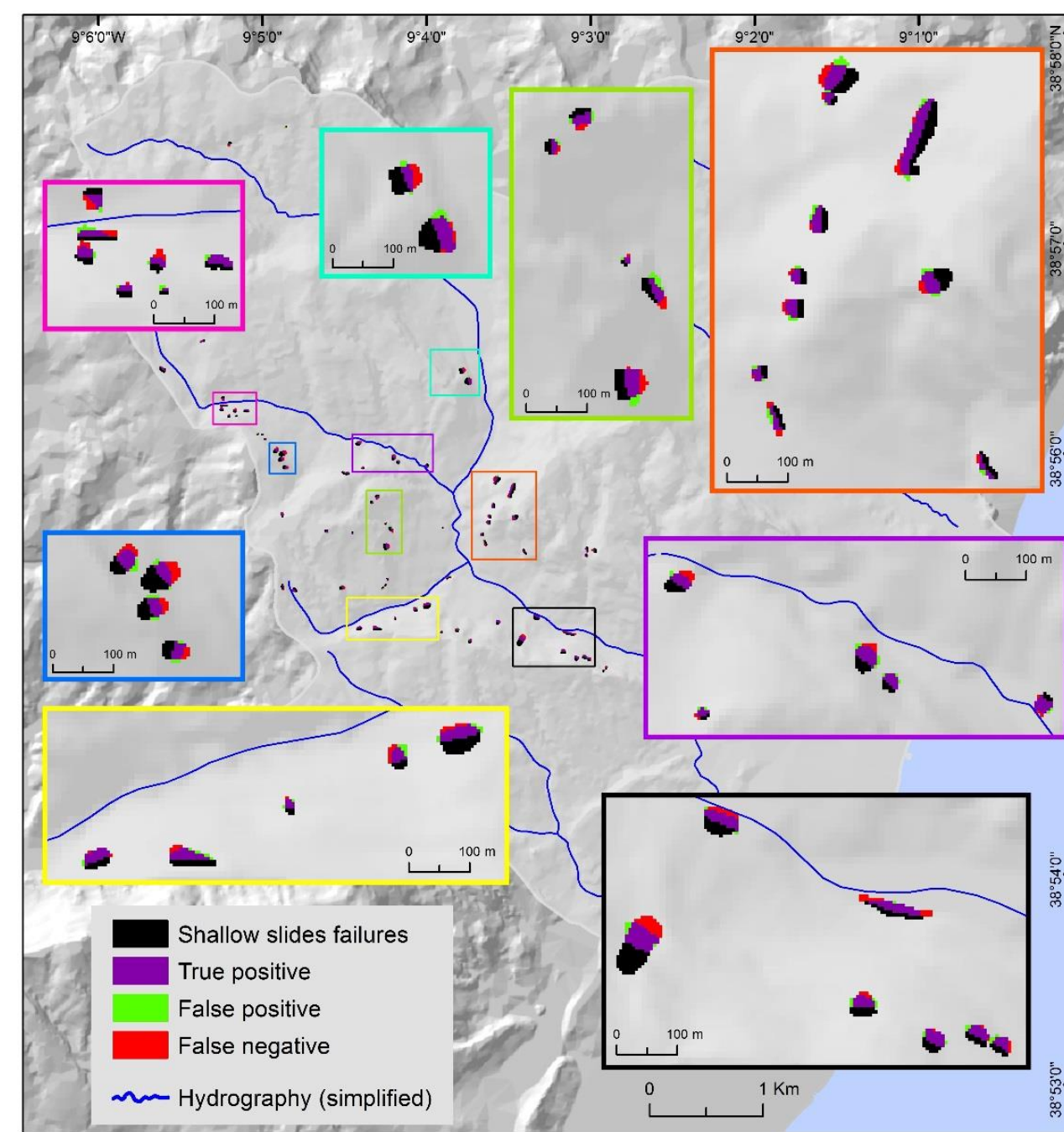
The VRMA is specified in degrees, ranging between -90° and 90° to compensate (+) and (-) slopes. This parameterization indicates that "negative slopes" have a lower cost, i.e., if there is a choice, the displaced mass will always go down the slope. Lower values (indicating steeper slopes) will favor the movement of the displaced mass. On the contrary, higher values will less likely promote the movement of the displaced mass in that direction.

#### 3.3.3. Temporal indexing and simulation

For the temporal indexing, we used the Markov chains analysis to estimate a transition area matrix, which records the number of cells that is expected to change location over a specified time.

The last stage refers to the CA simulation (i.e. to the spatial distribution of the landslide displaced mass) and uses the cost grid surface generated through the algorithm Path Distance and rescaled in order to represent a probability surface – which will inform about the likely travelling direction (according to the predefined transition rules) – and also the Markovian transition matrix file with the number of cells that will transit to the landslide accumulation zone. The algorithm runs iteratively over the transition map until the total number of cells (which are expected to transit) is allocated. In total, 10 simulations were performed as result of a maximum selection of 10 iterations.

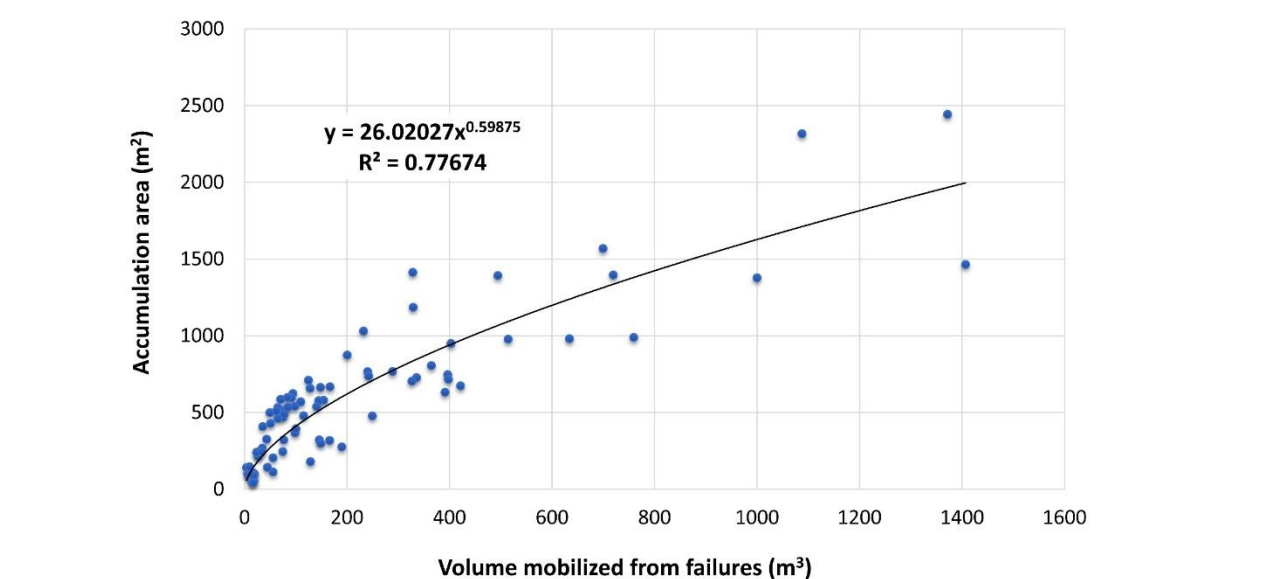
The validation of the 10 generated models, concerning the 10 iterations, was accomplished by comparing the results with the real accumulation area of the 81 landslides and, consequently, the estimation of the percentage of real accumulation area classified as true positive. Therefore, we verified that the simulation producing the best results comes from the selection of 5 iterations (Figure 9), with the modelling result validating 77% of the real accumulation area.



**Fig. 9** - CA modelling for shallow slides run out generated with 5 iterations.

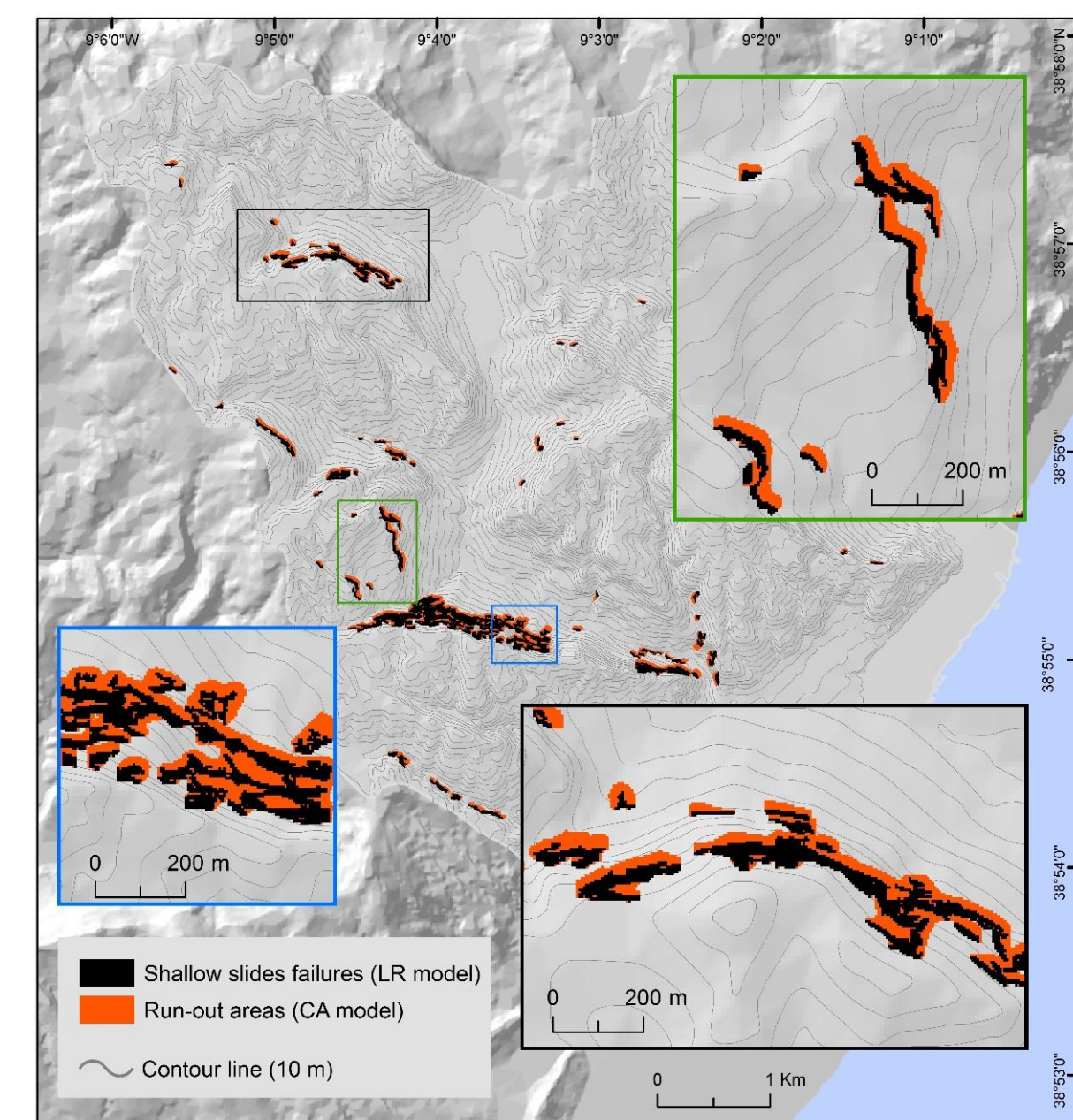
### 3.4. Susceptibility assessment of shallow slides failures and run-out, at the basin scale, by combining data-driven and simple CA models

The shallow slide susceptibility map including both failure and run-out areas was constructed for the entire basin following the next steps: 1) Estimation of the debris volume (Surdeanu, 1986) mobilized from failures, as well as the accumulation area, for each one of the 81 shallow slides inventoried in the study area; 2) Evaluation of the correlation between the debris volume mobilized from failures and the corresponding accumulation area (Figure 10);



**Fig. 10** - Relation between the debris volume mobilized from failures and the accumulation area, for the 81 shallow slides

3) Selection of 1% of the basin area with the highest values of spatial probability for failure (LR model). In addition, the areas with less than 500 m<sup>2</sup> were excluded in order to obtain spatially consistent zones, since it is assumed that isolated small groups of cells may not have a significant meaning for the susceptibility assessment at the basin scale. These procedures resulted in 83 new potential failure zones. 4) Estimation of the debris volume mobilized from failures defined in 3) and execution of equation estimated in 2), to calculate the corresponding accumulation areas. 5) Execution of the Markov chain analysis and CA model (5 iterations), for the potential failures, to evaluate the spatial extension of the run-out (Figure 11).



**Fig. 11** - Shallow slides susceptibility model at the basin scale, including the failures and run-out areas.

## 4. Final considerations

- The CA model validates 77% of the real accumulation area. The false negative rate (23%) is mainly due to the underestimation of the run-out distance, which is likely to be related to problems in the delimitation of the real accumulation areas at the time of field surveying.
- In terms of absolute error, evaluated by comparison between real and simulated run-out distances, a maximum of 20 m was recorded, with the mean absolute error being about 4.5 m.
- Considering the debris volume mobilized from failures and the accumulation area for the 81 shallow slides, we found that the correlation between these two parameters is quite significant, as demonstrated by the coefficient of determination ( $R^2 = 0.78$ ).
- When the simulation is performed at the basin scale, for the potential failures defined from the LR model, it is necessary to keep in mind that the accumulation area may also be underestimated.
- The integration of shallow slide failures with the areas potentially affected by the mobilized debris, besides ensuring a higher robustness of the susceptibility model, compared to the single definition of failures, also allows safeguarding the downstream areas providing tools for further susceptibility studies.
- In a last analysis, the susceptibility assessment of shallow slides with LR and a simple CA model allows the production of maps, achieved through simple and low-cost methods, where the failures are integrated with the areas potentially affected by the travelling material.
- The data required for modelling derives almost exclusively from the DTM, which enables the application to large areas with limited information. For this very reason, the quality of the DTM is crucial to obtain reliable results.

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**Acknowledgments:** This work was financed by national funds through FCT—Portuguese Foundation for Science and Technology, I.P., under the framework of the project BeSafeSlide—Landslide Early Warning soft technology prototype to improve community resilience and adaptation to environmental change (PTDC/GES-AMB/30052/2017). S. C. Oliveira has a Postdoctoral Grant (SFRH/BPD/85827/2012) funded by the Portuguese FCT. Research Unit UID/GEO/00295/2019.